

Flood Exposure Assessment of Electrical Substations in Iowa Using Geospatial Service-Area and Influence-Zone Modeling

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Abstract

Flooding poses a growing risk to electric substations, yet statewide assessments often fail to connect facility exposure with the spatial context of service territories, communities, built environments, and grid infrastructure. This study develops a data-driven geospatial framework to assess direct and indirect flood impacts on electrical substations across Iowa under 50-, 100-, and 500-year flood scenarios. The framework combines footprint-level inundation analysis with county aggregation, electric service boundaries (ESB), influence zones, demographic and energy-burden indicators, kernel density mapping, and allocation-sensitivity checks. Results show that exposed substations increase from 108 to 226 across the scenarios, with deeper and broader within-site inundation under larger events. Under the 500-year scenario, direct exposure affects 12.83% of substations, but affected service territories contain 66.27% of Iowa's population, 68.03% of statewide building footprint area, and 46.59% of grid-line length. Influence zone results show that impacted substation-centered zones contain 20.51% of the statewide population and remain above the statewide energy-burden average. Exposure concentrates along eastern and southeastern Iowa near the Mississippi corridor, extends into western and northwestern border transmission corridors, and appears as a strong urban built-environment hotspot in Polk County. Sensitivity results show that building-area exposure is the most transferable indicator between ESB and influence frameworks, while grid-line exposure is more boundary-dependent. The framework identifies priority substations where flood exposure intersects with broader regional consequence potential.

Keywords: Electrical Substations, Power Grid Resilience; Flood Hazard Assessment; Critical Infrastructure; Electric Service Boundaries; Socio-Economic Vulnerability; Resource Allocation; Spatial Exposure Modeling

1. Introduction

Electric power systems are foundational to the functioning of modern society because they support essential services such as healthcare, communications, food preservation, water treatment, emergency response, and economic activity. When electricity infrastructure fails, the consequences are rarely limited to the damaged facility itself; prolonged outages can disrupt interdependent systems and affect communities well beyond the immediate location of infrastructure failure (USGCRP, 2023; DOE, 2024). As climate-related hazards place growing stress on critical infrastructure, understanding the exposure and resilience of electric power systems has become increasingly important.

Among weather-related hazards, flooding poses a particularly significant threat to electric power systems because floodwater can damage substations, force facilities to be de-energized, interrupt transmission and distribution operations, restrict physical access for inspection and repair, and delay service restoration (Los Alamos National Laboratory [LANL], 2017; Karagiannis et al., 2019). Flood events can also disrupt transportation networks, telecommunications facilities, water systems, and emergency response services, and power outages can further reduce the functionality of these interconnected systems (Cha et al., 2025; Yan et al., 2025; Allen et al., 2025; Yildirim et al., 2023). Inland flooding is therefore a major concern for electric power infrastructure resilience and community-level risk planning (Costa & McAllister, 2017).

Across the United States, climate change has contributed to more frequent and intense hydrological extremes, including heavy precipitation, riverine flooding, and prolonged inundation events that threaten critical infrastructure systems (Mallakpour and Villarini, 2015; USGCRP, 2023). The Intergovernmental Panel on Climate Change reports that extreme precipitation events have increased in both frequency and magnitude across much of North America, heightening flood exposure for transportation, water, communication, and energy infrastructure (IPCC, 2023). In recent decades, flooding has become one of the costliest and most disruptive natural hazards affecting infrastructure systems in the United States, causing extensive physical damage, prolonged outages, and substantial economic losses (NOAA, 2025; USGCRP, 2023). Iowa provides a relevant setting for evaluating flood exposure and resilience of electric power infrastructure because the state has experienced repeated major flood disasters, including the historic Midwest floods of 1993, 2008, and 2019 (Weber et al., 2018; Demir et al., 2015).

Previous Iowa-focused studies have shown that flooding can affect built environments and property exposure (Alabbad & Demir, 2024), disrupt transportation networks (Duran et al., 2025a), and generate long-term economic and community recovery challenges after major flood events (Fung et al., 2020; Muñoz & Tate, 2016). Within this flood-infrastructure context, recent Iowa-focused energy research has demonstrated how geospatial flood-risk screening can support resilience and site-suitability analysis for wind-energy systems (Duran & Demir, 2026). Iowa's combination of riverine flood exposure, agricultural and rural service dependence, geographically dispersed electrical infrastructure, and expanding renewable-energy capacity makes energy-infrastructure resilience an important issue for regional risk assessment and planning.

Electrical substations are critical nodes within the power system because they transform voltage levels and enable power transfer between generation, transmission, and distribution

networks (U.S. Energy Information Administration [EIA], n.d.). Their network position makes them high-consequence assets: when floodwaters damage or force the shutdown of a substation, service interruptions can extend beyond the facility footprint by disrupting connected lines, altering power-flow patterns, and increasing outage extent across the surrounding grid (Los Alamos National Laboratory [LANL], 2016; Karagiannis et al., 2019). Flood exposure is especially concerning because substations contain dense concentrations of sensitive electrical equipment, including transformers, circuit breakers, control systems, and switchgear; inundation can cause equipment failure, require time-consuming inspection and cleanup, delay restoration, and amplify socioeconomic impacts for residential, commercial, industrial, and agricultural customers (Asaridis et al., 2025).

Previous research has advanced flood-related power-system resilience through asset-level damage modeling, network-based outage analysis, and optimization of protective investments. Substation-focused studies have linked flood forecasts (Demiray et al., 2024), equipment locations, and mitigation strategies to estimate physical impacts and improve resilience planning (Souto et al., 2022), while broader fragility-modeling research has emphasized the need to relate climate-related hazard intensity to damage probabilities, service disruption, and adaptation decisions for power-grid assets (Karagiannakis et al., 2024; Carson et al., 2018). Recent optimization studies have further shown how temporary flood-mitigation resources and substation-hardening investments can be prioritized to reduce expected load shedding and incorporate equity considerations into grid-resilience planning (Austgen et al., 2024; Toplu-Tutay et al., 2024). However, these approaches require detailed power-flow models, network topology, component fragility functions, or utility operating data that are not always publicly available for statewide assessments.

In parallel, GIS-based approaches have been widely used to integrate hazard layers, infrastructure inventories, socioeconomic indicators, and decision-support metrics for flood-risk assessment, resilience planning, and risk communication (Xiang and Demir, 2022). For example, GIS-based and multi-criteria frameworks have supported flood-risk mapping and mitigation prioritization (Rincón et al., 2018; Doorga et al., 2022; Duran et al., 2025b), spatial exposure and accessibility analysis for communities and critical facilities (Rentschler et al., 2022; Loreti et al., 2022), community- and infrastructure-level flood risk quantification (Alabbad et al., 2024), and urban social–ecological–technological vulnerability assessment (Duran et al., 2026). Within power-system planning, GIS-based proximity modeling has also been used to approximate primary substation service regions and support spatial allocation decisions (Bosisio et al., 2022).

These studies show that geospatial methods can translate complex flood hazards into actionable infrastructure and community-impact information (Shaid et al., 2023). What remains less developed is a transparent, data-driven approach that links substation flood exposure to spatially explicit community consequences, especially population exposure, building impacts, dependent infrastructure, and energy-burden-related vulnerability. This gap is important because energy-insecurity research shows that low-income households and communities with high energy burdens face greater difficulty preparing for, coping with, and recovering from power disruptions (Hernández, 2016; Bednar & Reames, 2020).

To address this gap, this study develops a scalable GIS-based framework for assessing direct and indirect flood impacts on electrical substations across Iowa. Direct exposure is

quantified by intersecting refined substation footprints with FEMA flood hazard datasets for 50-year, 100-year, and 500-year flood scenarios, using inundation extent, flood depth, and exposure variability to characterize facility-level vulnerability. Indirect consequences are estimated through substation-centered influence zones that approximate areas potentially associated with individual substations and enable assessment of exposed populations, buildings, dependent power-line infrastructure, and community energy-burden characteristics without requiring proprietary utility service-territory data. The overarching goal is to provide a transparent statewide screening framework that connects flood-exposed substations with community-level consequence indicators, helping identify locations where infrastructure exposure may coincide with disproportionate social, building, and infrastructure impacts and therefore warrant further engineering assessment, emergency planning, or resilience investment.

2. Methodology

This study uses a spatial exposure framework to examine how flooding intersects substations in Iowa and how those exposed facilities relate to surrounding population, buildings, and transmission-grid. The workflow includes footprint-based flood exposure analysis, county-level aggregation, ESB analysis, substation influence-zone assessment, kernel density visualization, and a sensitivity analysis.

2.1. Study Area

The state of Iowa was selected as the case study area because of its distributed substation network, riverine floodplain system, and the contrast between urban demand centers, agricultural regions, and border transmission corridors. Iowa is repeatedly exposed to riverine and flash-flood hazards because of its low-gradient Midwestern landscape, seasonal heavy rainfall, and major river systems, including the Mississippi and Missouri Rivers (Dirmeyer & Kinter, 2010; USGS, 2010; Zogg, 2014). Statewide analysis preserves multiple spatial units, including substation footprints, counties, electric service boundaries, substation influence zones, census geographies, building footprints, and transmission-grid features. This structure links facility-level flood exposure to broader population, built-environment, energy-burden, and grid-infrastructure indicators.

Figure 1 illustrates the county-level electric-infrastructure inventory used to frame the statewide analysis. The two numeric maps, substation count and intersected transmission-grid length, were classified using the natural breaks method (Jenks, 1967). Figure 1a shows total substation counts by county. Polk and Linn counties, which contain the Des Moines and Cedar Rapids metropolitan areas, fall in the highest substation-count class and represent facility-dense urban infrastructure settings. Figure 1b shows the dominant substation-voltage class by county. The 69 kV class, commonly associated with sub-transmission or lower-transmission networks, is dominant in 77 counties, which indicates that much of Iowa's county-level inventory is organized around an intermediate voltage layer (U.S. Department of Energy, 2023).

In contrast, 161 kV dominance is limited to four counties in central and north-central Iowa, including Polk County. Figure 1c shows intersected transmission-grid length by county and reveals a contrast with the substation-count pattern. Polk and Linn also have high grid-line lengths, so these counties combine dense substation inventories with substantial transmission

presence. Woodbury and Plymouth, however, are not in the highest substation-count class but fall in the highest grid-length class along Iowa’s western boundary. These counties represent border transmission corridors that support regional energy transfer. The baseline inventory therefore establishes the statewide infrastructure context: dense urban substation clusters in Polk and Linn counties, long western transmission corridors in Woodbury and Plymouth counties, and a broad 69 kV-dominant network. This structure provides the basis for evaluating flood exposure across both facility-dense urban areas and corridor-oriented grid regions.

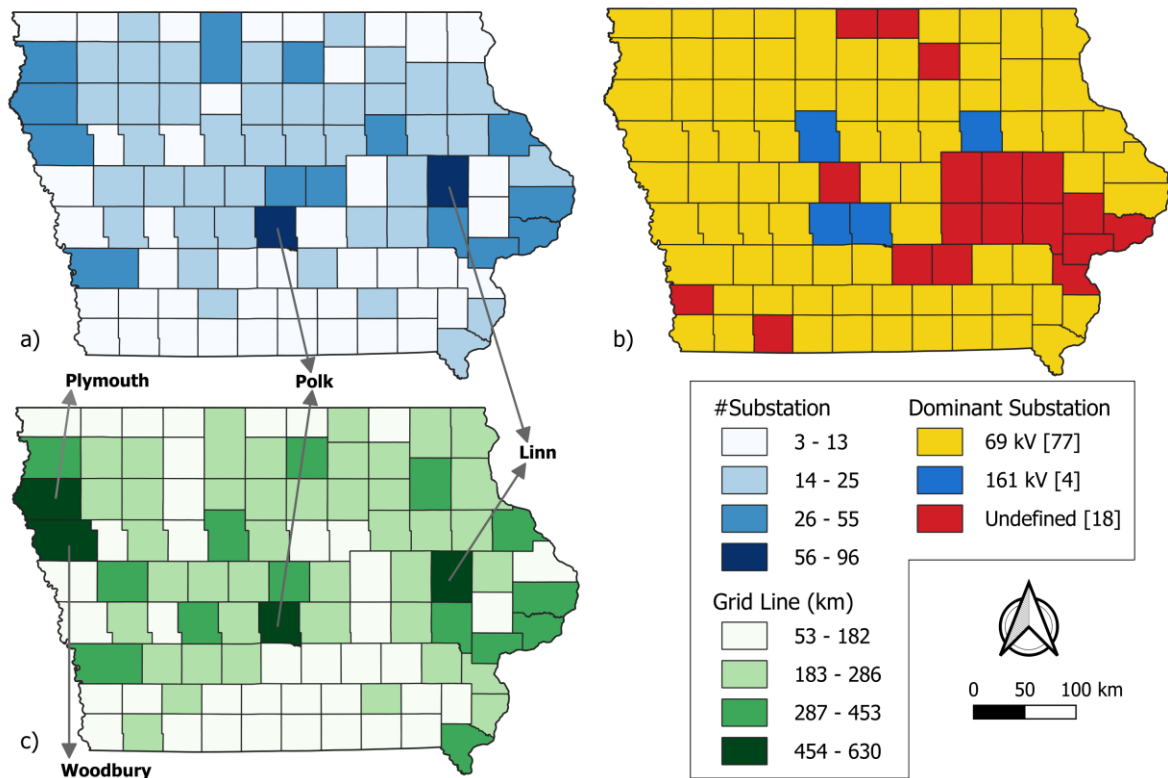


Figure 1. County-level electric-infrastructure inventory in Iowa showing (a) substation count, (b) dominant substation-voltage class, and (c) intersected transmission-grid length.

2.2. Data Sources and Geospatial Preprocessing

The study integrates flood maps, substation footprints, transmission grid lines, electric service boundaries, demographic distribution, building footprints, county boundaries, and socio-economic indicators. Table 1 summarizes the datasets used in the analysis, their spatial form, source, baseline inventory, and role in the workflow.

Flood hazard inputs consist of flood-depth grids for 50-, 100-, and 500-year flood scenarios, corresponding to 2%, 1%, and 0.2% annual-chance flood conditions (Holmes & Dinicola, 2010; FEMA, n.d.). The flood products were organized as 55 HUC8-based tiles for each scenario, providing statewide coverage through watershed-based flood-map units. These 55 HUC8-based tiles, derived from HEC-RAS and MIKEFLOOD hydraulic models, were obtained from the Iowa Geospatial Data Clearinghouse and build upon established statewide inundation mapping efforts, including flood map visualization and flood cyberinfrastructure for Iowa (Gilles et al., 2012; Baydaroglu et al., 2022; Yesilkoy et al., 2024; Iowa GDC, 2023). Iowa flood mapping is supported by LiDAR-based terrain data and hydraulic modeling in

which terrain representation, stream geometry, flow conditions, and boundary assumptions are used to estimate flood extent and depth (Iowa DNR, 2024).

Table 1. Input datasets used in the statewide substation flood-exposure assessment.

Dataset	Spatial form	Source / version	Coverage / baseline	Role in analysis
County boundaries	Polygon	U.S. Census TIGER/Line, 2020	Iowa, 99 counties	Defines study area, county-level aggregation units, and reference boundaries
Flood hazard layers	Raster flood-depth grids	HEC-RAS and MIKEFLOOD flood hazard layers, Iowa Geodata, 2023	50-, 100-, and 500-year scenarios; 55 HUC8- tiles	Identifies exposed footprints, inundated area, depth, and coverage
Substation inventory	Point	HIFLD Electric Substations, 2023	1,762 substations	Provides facility locations and attributes
Substation footprints	Polygon	HIFLD inventory refined with OSM	Delineated substation footprint layer	Represents physical facility extents for direct flood-overlay analysis
Electric grid	Line	HIFLD Electric Transmission Lines, 2022; OSM electric-line features, 2026	22,390.9 km total line	Represents grid-line length within counties, ESBs, and influence zones
Building footprints	Polygon	OpenStreetMap, accessed 2026	506,914 buildings; 169.0 km ² footprint	Summarizes building count and footprint area in affected units
Population geography	Polygon	U.S. Census, 2020	Iowa statewide; 3,190,369 people	Allocates population to ESBs, and influence zones
Energy burden and electricity cost	Census tract attribute	DOE/NLR/Alliance SLOPE, 2022	Iowa statewide census-tract coverage	Provides socio-economic energy-context
Electric service boundaries	Polygon	IUC-ESBs, 2022	1,360 service-area polygons	Aggregates exposed substations and context by utility territory

Electric infrastructure datasets merged Homeland Infrastructure Foundation-Level Data (HIFLD), OpenStreetMap (OSM), public electric-line records, and true-color imagery. HIFLD Electric Substations provided the initial statewide point inventory and voltage attributes, while HIFLD Electric Power Transmission Lines served as the primary transmission-line layer (HIFLD, 2022; 2023). Because the baseline substation inventory was strictly point-based, facility footprints had to be delineated prior to the flood-overlay analysis. HIFLD points were matched with OSM substation features, visible electrical equipment, fenced facility boundaries, and nearby grid-line connections using true-color imagery. Where mapped OSM geometries matched the visible substation extents, they were retained; conversely, where mapped geometries were missing, incomplete, or displaced, facility boundaries were manually corrected in QGIS. Missing or incomplete grid-line features were similarly verified against

OSM and imagery, resulting in a final combined grid-line layer that incorporated features mapped across varying network scales. This combined layer was used to calculate grid-line length within counties, ESBs, and substation-centered zones.

County boundaries, CENSUS population, OpenStreetMap building footprints, DOE/NLR LEAD tract-level energy indicators, and Iowa Utilities Commission (IUC) ESBs were used to describe the spatial context around exposed substations. Building count and building footprint area were retained separately because they represent different forms of built-environment concentration, while energy burden and electricity cost were added as socio-economic energy-context variables. All datasets were projected to a common coordinate system for Iowa-scale area and length calculations and processed in QGIS using a SpatiaLite workflow. Geometry validation, spatial indexing, SQL joins, and scenario-specific query tables were used to maintain consistency across the 50-, 100-, and 500-year scenarios. The workflow separated direct footprint exposure from aggregation, prevented duplicate ESB assignments, clipped grid lines to affected units, linked buildings to ESB and Voronoi polygons, and allocated population from census geography.

Due to data limitations regarding operational electric-service configurations in public geospatial repositories, several key assumptions were incorporated into the analytical framework. Substation exposure was based on the intersection between refined facility footprints and flood-depth grids, so the results identify spatial footprint exposure rather than confirmed equipment failure, outage occurrence, or service loss. Although the footprint layer was manually refined using mapped features and imagery, small boundary errors may remain where facilities are partially obscured, share space with adjacent electrical equipment, or lack complete mapped geometry. ESBs were treated as utility-territory polygons rather than feeder-level customer-service areas; substations were assigned once to prevent duplicate counting in overlapping service areas, and ESBs without assigned substations were excluded from closure-rate calculations. Population, buildings, energy-burden indicators, and grid-line length were interpreted as spatial context around exposed infrastructure, not as direct measures of interrupted customers, damaged buildings, or failed electric lines. The combined grid-line layer represents mapped line presence but does not include power flow, switching configuration, redundancy, restoration behavior, or operational status. These assumptions frame the analysis as a reproducible geospatial flood-exposure screening rather than an outage or reliability simulation.

2.3. Substations Flood Analysis

Substation flood analysis was the first analytical step following dataset preparation, converting scenario-based flood-depth raster into facility-level exposure records used in the subsequent spatial analyses. It was conducted at the footprint scale to accurately capture the physical area, the share of the facility affected, and flood-depth variation across the facility boundary. In this study, closure refers to footprint-level exposure, meaning a substation was classified as closed if its delineated footprint intersected the mapped flood extent for a given scenario.

For each flood scenario, raster tiles were combined into specific flood layer, preserving the watershed-based structure of the source products prior to overlaying them with the substation footprints. Before zonal statistics were calculated, the raster files were restricted to inundated cells by removing non-flood values and no-data cells. This distinction is critical because a

substation footprint can contain both inundated and dry areas; including dry cells in the calculation artificially reduces the mean depth and misrepresents the actual flood conditions within the affected portion of the facility. The full footprint area was retained separately to calculate the coverage ratio.

For each substation and flood scenario, zonal statistics were calculated from the flood-depth raster using the delineated footprint polygon as the analysis zone. The workflow recorded a binary exposure flag, inundated cell count, mean depth, maximum depth, depth variance, inundated area, and footprint coverage ratio. The mean depth represents the average inundation within the flooded portion, while the maximum depth identifies the deepest intersecting raster cell and depth variance was retained to capture within-footprint variation. Inundated area and coverage ratio were reported together to describe the spatial extent of footprint exposure, differentiating between mapped inundations that involved a small edge contact versus a larger portion of the facility. The scenario-level closure percentage was calculated using Equation 1.

$$Closure\ Percentage_s = \left(\frac{N_{closed_s}}{N_{total}} \right) \times 100 \quad Eq. 1$$

where $N_{closed,s}$ is the number of substations whose footprints intersect the flood layer under scenario s , and N_{total} is the total number of substations in the statewide inventory. A cross-scenario consistency check was applied to the 50-, 100-, and 500-year closure flood scenarios. Because these scenarios represent progressively larger annual-chance flood events, a footprint exposed in a lower-return-period layer was expected to remain exposed in the higher-return-period layers. Non-monotonic records were reviewed as potential raster or model-transition artifacts caused by tile boundaries or resolution limitations. Between the 50- and 100-year layers, 6 substations showed inconsistent classifications (4 of which were caused by single-cell footprint intersections at the edge of the facility). Between the 100- and 500-year layers, 21 inconsistencies were identified, including five cases with larger inundated footprint coverage. After review, records attributable to classification artifacts were adjusted to preserve logical consistency across flood scenarios, using the lower-return-period exposure as the reference condition. This procedure retained the expected nesting of flood exposure while documenting the treatment of non-monotonic raster artifacts for transparency.

The finalized closure classifications served as the basis for the remaining spatial assessments. County summaries use these locations to identify administrative exposure patterns, ESB analysis aggregates them within utility-territory polygons, tessellation analysis transfers the closure classification to influence zones, and kernel-density mapping visualizes statewide clustering. By establishing closure at the footprint level, the subsequent spatial analyses remain securely tied to direct facility exposure rather than relying solely on abstract point locations or broad service areas.

2.4. County-level Aggregation

County-level aggregation translates footprint-level exposure results into administrative planning geography. This framework summarizes flood closure and population characteristics. By using counties as the primary spatial unit, flood-exposure patterns could be systematically evaluated within the broader infrastructure geography. Each substation was spatially assigned

to a county to prepare summaries for substation count, dominant substation type, transmission grid-line length, population, and flood-exposure metrics. The baseline variables established the county inventory context, while flood-specific summaries were derived directly from the footprint-level closure classifications developed in Section 2.3. For each flood scenario, both the total number of closed substations and the closure percentage relative to the county's total inventory were calculated. Closure count indicates the absolute number of affected facilities, whereas closure percentage indicates the relative share of the compromised inventory. This distinction is important, as counties with extensive substation networks may exhibit high closure counts but moderate closure percentages, while counties with sparse inventories may experience high closure percentages from the loss of only a few exposed facilities.

Bivariate mapping was employed to visualize county population and closure percentage within the same cartographic frame. While the closure percentage normalizes flood exposure against the size of the county's infrastructure inventory, the population data provides a broader social context. Mapping these variables enables the immediate identification of regions where high infrastructure exposure intersects with large population totals. This approach serves as an effective spatial screening tool; bivariate choropleths are uniquely suited for this purpose because they display two spatial indicators within the same geographic unit, facilitating direct comparison across combined classes (Biesecker et al., 2020). Furthermore, the natural breaks classification method was applied to both variables to accurately reflect the uneven distributions of county-level populations and closure percentages (Jenks, 1967).

2.5. Electric Service Boundary Analysis

Electric service boundary (ESB) analysis evaluated flood-exposed substations within available utility service-area polygons. While counties provide administrative geography, ESBs offer a utility-territory framework for summarizing exposed substations and their associated surrounding populations, buildings, and grid infrastructure. Substations were spatially assigned to ESBs using a primary-assignment rule based on the largest intersecting boundary to prevent duplicate counting in overlapping areas. Each ESB was then evaluated across the 50-, 100-, and 500-year flood scenarios, and then an ESB was classified as affected if it contained at least one closed substation to calculate closure percentages for that specific inventory.

ESBs with at least one assigned substation were used for exposure-context summaries. For affected ESBs, the analysis aggregated surrounding contextual metrics such as population, building count, building footprint area, and transmission grid-line length. Population estimates were derived from census blocks via area-weighted allocation, distributing a block's population proportionally based on the area located inside the ESB (Goodchild & Lam, 1980). Building counts and footprint areas were extracted from geometries intersecting the affected ESB, while transmission grid-line lengths were calculated by clipping line features to the ESB boundary and summing the internal segments.

The ESB framework links footprint-level substation closure to utility-territory geography; however, the resulting summaries should be interpreted as spatial exposure estimates, not feeder-level service assignments. A single service boundary can include multiple substations, overlapping ESBs can indicate more than one possible substation association, and ESBs with no assigned substations cannot be used to calculate internal closure rates. These limitations define the analytical role of the ESB model: it identifies affected utility territories and

characterizes their population, building, energy-burden, and grid-infrastructure context, but it does not assign individual customers or assets to specific substations. This limitation is common in critical-infrastructure recovery studies, where true source–sink relationships are often unavailable, incomplete, proprietary, or operationally dynamic, requiring spatial allocation methods for screening-scale impact assessment (Pala et al., 2014). Therefore, an additional spatial perspective is needed to evaluate substation-associated exposure using a consistent allocation rule.

2.6. Substation Influence-Zone Delineation and Exposure Assessment

Substation influence-zone assessment was used to create a substation-centered allocation framework for summarizing exposure context around individual facilities. After footprint-level closure was identified, each closed substation required an associated spatial unit so that surrounding population, buildings, energy-burden indicators, and grid-line length could be summarized consistently. Because detailed feeder assignments, customer-to-substation relationships, switching behavior, and operational service configurations were not available in the public datasets, the Voronoi-based zone framework was used as a transparent nearest-substation allocation rule for screening-scale exposure assessment.

The spatial allocation approach used in this study follows infrastructure-risk and service-area studies that use estimated service areas to relate substations and other infrastructure assets to surrounding population, demand, and disruption potential (Pala et al., 2014; Poljanšek et al., 2010; Pant et al., 2018). It also aligns with power-system planning work that applies Voronoi diagrams to approximate primary substation service areas and loading conditions (Bosisio et al., 2022). Geometrically, each substation midpoint was used as a generator in the Voronoi tessellation. Each Voronoi polygon defines the area closer to its parent substation than to any other substation. This creates a standard geometric partition of space based on nearest generating points (Aurenhammer, 1991). After generation, the polygons were clipped to the Iowa boundary and joined to the attributes of their parent substations. This produced smaller polygons in areas with dense substation spacing and larger polygons where substations are farther apart, reflecting the relative spacing of the statewide substation network.

Each Voronoi polygon then inherited the closure status of its parent substation, and polygons linked to closed substations were treated as affected influence zones for the corresponding flood scenario. Within these affected zones, population, building count, building footprint area, energy-burden indicators, and transmission grid-line length were summarized using the same spatial-overlay logic applied in the ESB analysis: population was allocated from intersecting census geographies through areal interpolation (Goodchild & Lam, 1980), buildings were summarized from intersecting footprints, and transmission grid-line length was calculated by clipping line geometries to the Voronoi boundaries and summing only the portions located inside each affected influence zone.

The non-overlapping structure of the Voronoi-derived zone layer is central to its role in the study. Each area is assigned to one nearest-substation zone, allowing the same contextual variables used in the service-boundary analysis to be summarized through a consistent facility-centered allocation framework. This creates a second spatial perspective for evaluating flood exposure, complementing the utility-territory approach represented by the ESBs. Comparing results across these two frameworks helps show how estimates of affected population,

buildings, energy burden, and infrastructure change depending on the spatial unit used for aggregation. The influence-zone assessment is therefore interpreted as a nearest-substation exposure framework that provides additional context for understanding potential impacts around closed substations, not as a representation of actual feeder-level service areas.

2.7. Kernel Density Analysis of Flood-Exposed Substations

Kernel density estimation (KDE) was used to visualize the regional concentrations of flood-exposed substations. Point maps identify individual exposed facilities, but regional clustering patterns can be difficult to interpret from point locations alone. KDE addresses this limitation by transforming discrete point observations into a continuous density surface, where each point contributes influence within a defined search radius. This method is widely used to estimate continuous intensity from point data, with bandwidth controlling the degree of smoothing across the resulting surface (Silverman, 1986).

The KDE workflow utilized to generate both unweighted and weighted density surfaces. The unweighted surface assigned equal weight to each exposed substation and therefore represented the spatial concentration of flood-exposed facilities. For the weighted surfaces, each exposed substation was assigned a influence-zone attribute, such as associated grid-line length, building footprint area, or building count. As a result, the weighted KDE maps identify areas where flood-exposed substations coincide with higher surrounding exposure context. KDE therefore serves as a visual synthesis tool that links the facility-level closure layer with the exposure indicators. The KDE surface for exposed substations was calculated using Equation 2.

$$\hat{D}(x) = \sum_{i=1}^n w_i K\left(\frac{d_i}{h}\right) \quad \text{Eq. 2}$$

where $\hat{D}(x)$ is the estimated density at location x , w_i is the weight assigned to exposed substation i , d_i is the distance from location x to substation i , h is the bandwidth, and K is the kernel function. A quartic kernel was applied because it assigns greater influence on observations near the cell center and reduces that influence smoothly to zero at the search-radius limit. For the unweighted density surface, $w_i = 1$, whereas for the weighted surfaces, w_i was defined using the respective influence zone attribute assigned to each flood-exposed substation.

2.8. Sensitivity and Consistency Analysis

Sensitivity analysis was conducted to examine how ESB-based exposure estimates change under different approaches for defining an affected service boundary. Because the main ESB analysis used a binary rule, counting the full ESB context even if a small portion of its substations were exposed, an internal closure rate was calculated by Equation 3:

$$CR_{j,s} = \frac{C_{j,s}}{N_j} \quad \text{Eq. 3}$$

where $CR_{j,s}$ is the closure rate of ESB j under flood scenario s , $C_{j,s}$ is the number of flood-exposed substations, and N_j is the total number of assigned substations (excluding ESBs with no assigned substations). The two ESB exposure formulations were then compared to evaluate the sensitivity of the results to the affected boundary definition. The first formulation was the binary classification shown in Equation 4.

$$E_{j,s}^{binary} = \begin{cases} E_j, C_{j,s} > 0 \\ 0, C_{j,s} = 0 \end{cases} \quad \text{Eq. 4}$$

where E_j is the ESB-level exposure-context value, such as population, building count, building area, or transmission-line length. The second formulation was the closure-rate-weighted calculation shown in Equation 5.

$$E_{j,s}^{weighted} = E_j \times CR_{j,s} \quad \text{Eq. 5}$$

These results were used as a substation-centered comparison to the broader ESB-based allocation. This comparison examined how exposure-context results change when the same closed substations are summarized through two spatial aggregation frameworks. The influence-zone framework adds a facility-centered perspective, while the ESB framework represents affected utility-territory context. Population and built-environment transfers across these non-identical spatial units followed established principles of areal interpolation and spatial overlay (Goodchild & Lam, 1980).

Correlation between the ESB and influence-zone approaches was evaluated at the closed-substation level. For each closed substation, the value from its Voronoi polygon was compared with the closure-rate-weighted value of its assigned ESB. Spearman's rank correlation (ρ) was used as the primary measure because it compares the relative ordering of closed substations across the two frameworks and is appropriate when raw exposure values differ substantially in scale or distribution (Spearman, 1904), as shown in Equation 6:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \quad \text{Eq. 6}$$

where d_i is the difference between the Voronoi rank and the weighted ESB rank for closed substation i , and n is the number of closed substations. Pearson correlation (r) was calculated as a supplementary linear check to determine whether higher influence-zone exposure values corresponded to higher closure-rate-weighted ESB values for the same closed substations (Pearson, 1896; Kuckartz et al., 2013), as defined in Equation 7:

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad \text{Eq. 7}$$

where x_i and y_i are the influence zone and closure-rate-weighted ESB values for closed substation i , respectively, and $\bar{x}$ and $\bar{y}$ are their corresponding means. This sensitivity analysis

evaluated whether population, building count, building footprint area, and grid-line length were stable across the binary ESB, closure-rate-weighted ESB, and influence-zone aggregation frameworks.

3. Results and Discussion

This section presents substation flood exposure from direct facility inundation to broader spatial analysis using counties, ESBs, influence zones, and demographic, infrastructure, hotspot and allocation-sensitivity contexts.

3.1. Footprint-Level Flood Exposure

At the footprint scale, flood exposure was evaluated by intersecting delineated substation boundaries with the 50-, 100-, and 500-year inundation layers. A substation was classified as closed when any portion of its footprint intersected the corresponding flood layer. Table 2 summarizes the number of closed substations, inundation depth, flooded footprint coverage, and depth variance across the three scenarios.

The results show that direct footprint exposure increases steadily with flood magnitude. Closed substations rise from 108 in the 50-year scenario to 226 in the 500-year scenario, which corresponds to an increase from 6.13% to 12.83% of the statewide inventory. Therefore, direct exposure remains a relatively small share of all 1,762 substations, but the exposed subset more than doubles across the scenarios. This pattern indicates that larger flood events expand the number of facility boundaries reached by mapped inundation while still concentrating direct impacts within a limited portion of the statewide substation system.

The depth-related results show that this expansion is not only caused by additional shallow-edge contacts. Mean coverage depth more than doubles between the 50-year and 500-year scenarios and mean maximum depth approaches one meter in the 500-year scenario. These increases show that larger flood scenarios intensify the within-footprint water conditions at affected substations since if newly affected substations were mainly small edge contacts with shallow water, these average depth values would be expected to weaken. For infrastructure interpretation, this distinction is important because deeper water inside a facility boundary is more relevant to equipment interruption, safe access, inspection difficulty, and post-flood maintenance than the binary closure count alone.

Table 2. Footprint-level substation flood-exposure summary.

Metric	50-year	100-year	500-year
Closed substations	108	171	226
Closed substations (%)	6.13	9.70	12.83
Mean coverage depth (mm)	284.09	380.65	632.97
Mean maximum depth (mm)	498.46	615.82	944.91
Mean depth variance (mm ²)	53,381.82	30,526.46	38,649.49
Average areal coverage ratio (%)	40.73	51.15	63.36

Flooded footprint coverage also increases across the scenarios, from about 41% in the 50-year scenario to about 63% in the 500-year scenario. This indicates that larger events affect a broader share of each facility exposed, not just a larger number of facilities. These coverage

values are substantial for substation footprints because they indicate that many affected facilities are not limited to minor boundary contact; a large portion of the mapped site is exposed once closure occurs. Depth variance shows a more complex pattern. It decreases from the 50-year to the 100-year scenario, then increases again in the 500-year scenario. This non-monotonic result indicates that within-footprint depth variability does not scale directly with flood magnitude. The 100-year scenario has deeper and broader inundation than the 50-year scenario, but the lower variance suggests a more even distribution of flooded depths within affected footprints. Therefore, the most critical footprint-level cases are best identified by considering closure status, depth, coverage ratio, and internal depth variability together.

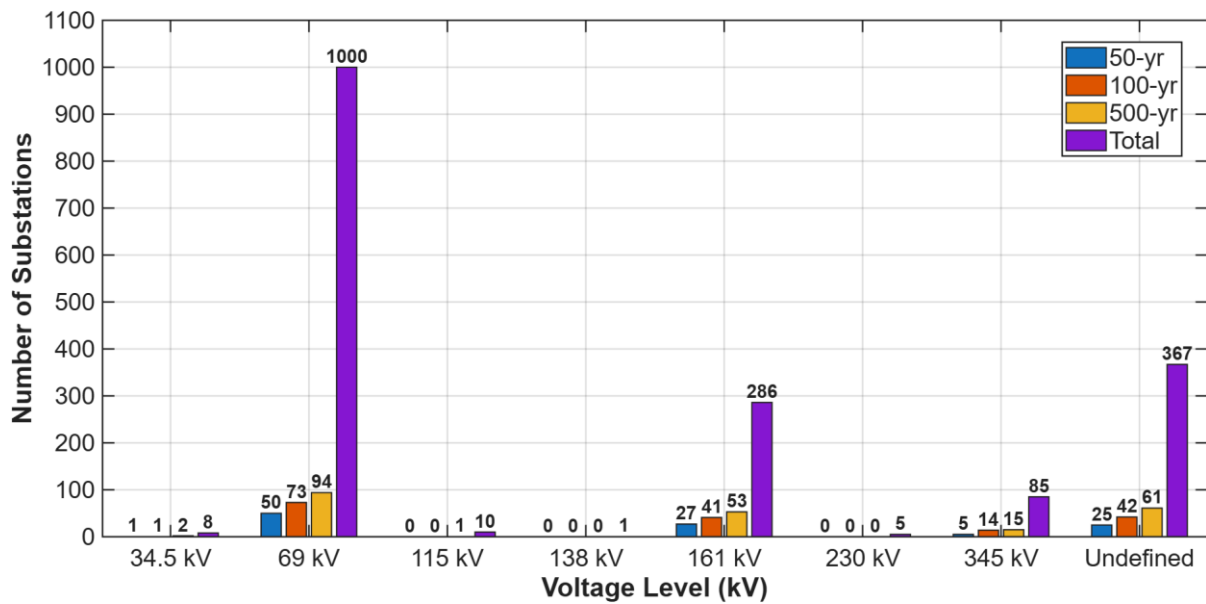


Figure 2. Voltage-class distribution of statewide substation inventory and closed substations under the 50-, 100-, and 500-year flood scenarios.

Figure 2 shows that the voltage-class pattern of footprint closure reflects both inventory size and relative exposure. The 69 kV class is the dominant layer in the statewide inventory, so it produces the largest number of closed substations in every scenario. However, its share of the closed set decreases from 46.30% to 41.59% across the 50- to 500-year scenarios, and its within-class closure rates remain below the statewide closure percentages in all three scenarios. This shows that the high number of 69 kV closures mainly reflects how common this class is in the inventory. Higher-voltage and undefined-voltage groups show the opposite pattern.

The 161 kV, 345 kV, and undefined-voltage classes contribute fewer closed substations by count, but they have higher relative exposure under the larger scenarios, reaching 18.53%, 17.65%, and 16.62% closure in the 500-year scenario, respectively. Smaller classes should be interpreted cautiously because percentage closure rates can appear large when the inventory size is limited, as seen for the 34.5 kV group, while the 138 kV and 230 kV classes have no closures. Consistent with this class composition, the mean nominal voltage of closed substations is higher than the statewide inventory average of 105.44 kV in all three scenarios, with values of 115.14, 127.93, and 123.50 kV. Because voltage class broadly reflects operating

level and transfer capacity, this result suggests that footprint exposure includes not only the dominant 69 kV class but also substations in higher-capacity voltage categories.

3.2. County-Level Closure Patterns

The county-level closure maps, shown in Figure 3, summarize flood-exposed substations within administrative boundaries under the 50-, 100-, and 500-year flood scenarios. Figure 3 shows that county-level involvement increases steadily across the flood scenarios. The 50-year scenario includes 108 closed substations across 48 counties, increasing to 171 closed substations across 55 counties in the 100-year scenario and 226 closed substations across 61 counties in the 500-year scenario. This progression shows that larger flood scenarios expand both the number of affected facilities and the number of counties with at least one exposed substation.

In Figure 3a, the 50-year scenario shows an east-central and eastern signal: Muscatine, Johnson, and Linn have the highest closure counts, with six closed substations each, while Butler, Bremer, Clay, Marshall, and Clinton each have four closures. However, the percentage values highlight a different severity pattern, with Butler at 26.67%, Bremer at 23.53%, and Iowa at 21.43% of their local inventories closed. In Figure 3b, the 100-year scenario strengthens both eastern and western signals. Pottawattamie and Muscatine become the leading counties by closure count, with 14 and 13 closed substations, followed by Polk with 12; at the same time, Butler reaches 40.0%, Pottawattamie 38.9%, and Muscatine 38.2% closure.

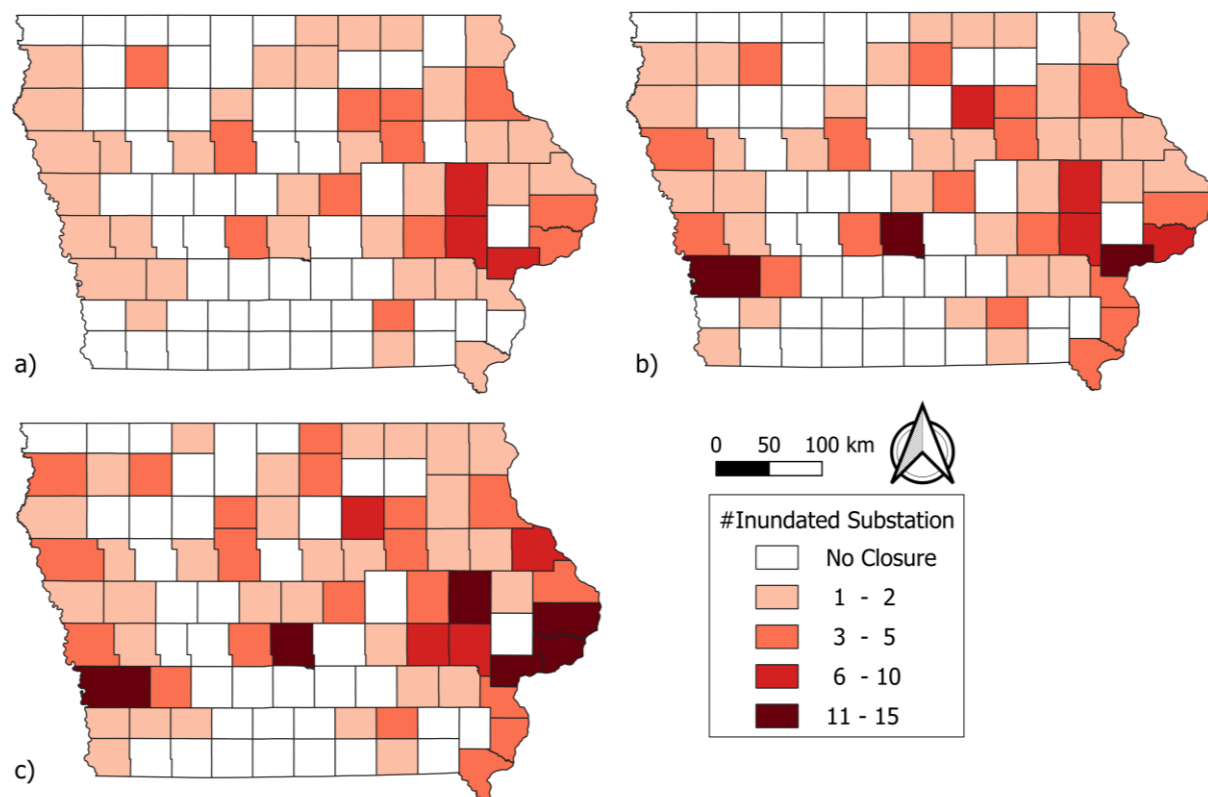


Figure 3. Number of inundated substations per county under the a) 50-, b) 100-, and c) 500-year flood scenarios.

Polk illustrates the contrast between count and percentage because its 12 closures represent 17.4% of a larger local inventory. In Figure 3c, the 500-year pattern becomes more concentrated along the eastern and southeastern corridors while selected western counties remain prominent. Pottawattamie has the highest closure count with 15 closed substations, followed by Muscatine with 14, while Clinton, Scott, and Polk each have 12. The percentage results further distinguish proportional local exposure: Butler reaches 46.7%, Iowa 42.9%, Pottawattamie and Harrison 41.7%, and Muscatine 41.2%.

The main county-level interpretation is that closure exposure is not controlled only by county inventory size. Large-inventory counties such as Polk, Linn, Johnson, and Scott contain many affected substations, but their closure percentages are moderated by the size of their full inventories. Counties such as Butler, Iowa, Harrison, Louisa, Humboldt, and Worth show the opposite condition: they have fewer total closures, but the affected facilities represent a substantial share of local substation infrastructure. Pottawattamie and Muscatine are the strongest combined cases because they rank high in both closure count and closure percentage under the larger scenarios. County aggregation therefore identifies where closure concentrations occur and where local inventory exposure is proportionally high, but additional spatial layers are needed to connect these closure locations with surrounding population, built-environment, service-territory, and grid-infrastructure context.

3.3. Electric Service Boundary Level Closure Analysis

In addition to the substation- and county-level results, the analysis was extended to electric service boundaries (ESBs) to evaluate how footprint-level closures appear within utility service territories. The ESB layer contains 1,360 service areas, but closure percentages were evaluated using the 408 ESBs that contain assigned substations. Figure 4 presents the percentage of assigned substations closed within each ESB under the 50-, 100-, and 500-year flood scenarios.

Figure 4 shows that ESB-level closure changes in both spatial extent and internal severity as flood magnitude increases. The number of ESBs with no assigned substation closure decreases from 338 in Figure 4a to 323 in Figure 4b and 308 in Figure 4c. In Figure 4a, higher closure classes appear mainly across eastern and northern Iowa, while much of the central-southern portion of the state remains in the No Closure or Low classes.

In Figure 4b, the ESBs affected expand, but the low-class changes slightly, from 31 to 29 ESBs. The larger shift occurs in the Medium and High classes, which increase from 30 to 42 ESBs and from 9 to 14 ESBs, respectively. Spatially, this appears as a continued high-closure presence along the western edge of the state, together with additional closure pockets in eastern Iowa. In Figure 4c, eastern closure pockets expand, while High-closure ESBs remain visible along the northwest and western boundary and appear in parts of the southern corridor. Across the 50- to 500-year scenarios, the low-class changes only from 31 to 33 ESBs, while the medium-class increases from 30 to 43 and the High class increases from 9 to 24. This pattern shows that larger flood scenarios are not simply adding lightly affected service territories; they are moving more ESBs into moderate and high internal closure categories.

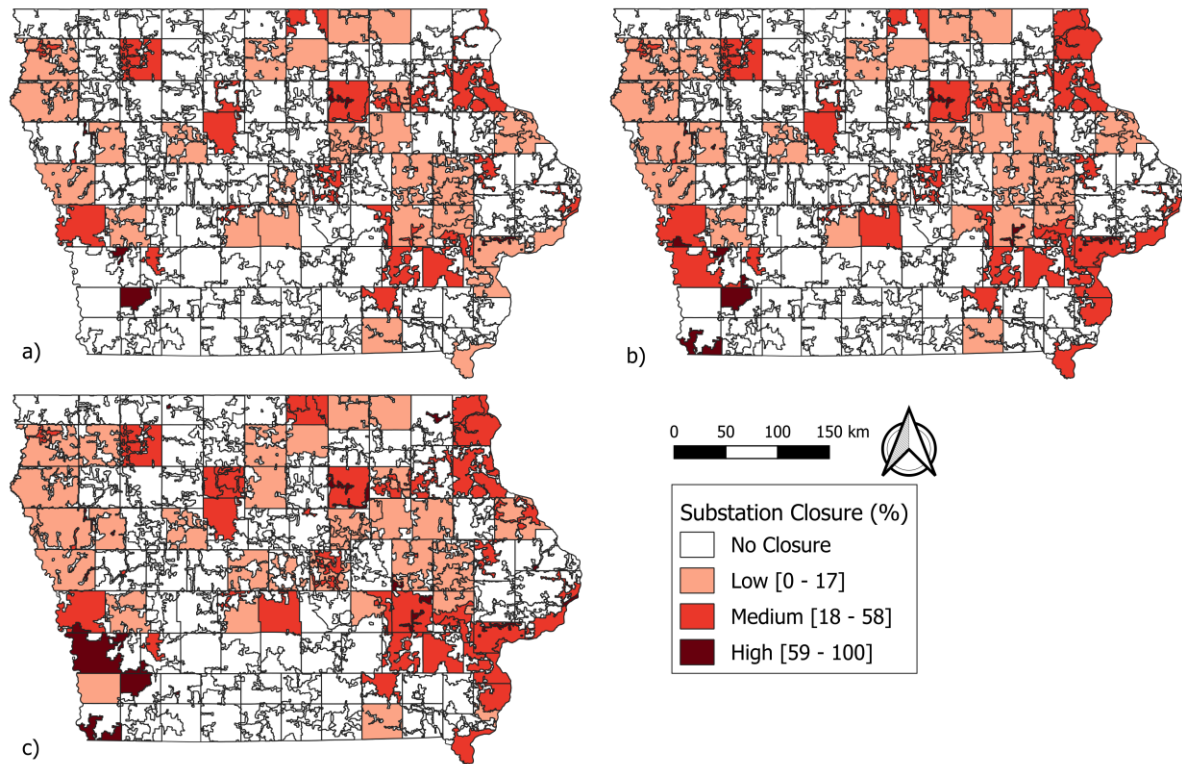


Figure 4. ESB-level substation closure percentage under the a) 50-year, b) 100-year, and c) 500-year flood scenarios.

Table 3. ESB-level closure and service-territory context metrics.

Metric	50-year	100-year	500-year
Affected service areas	70	85	100
Affected service areas (%ESBs with substations)	17.16	20.83	24.51
Average closed substations per affected ESB	1.54	2.01	2.26
Mean closure among affected ESBs (%)	29.76	35.26	40.99
Fully closed service areas	7	12	18
Fully closed service areas (% of affected ESBs)	10.00	14.12	18.00
Affected service-area extent (% of total ESB area)	29.05	35.09	39.14
Average service-area size per affected ESB (km ²)	600.02	596.94	565.93
Building count inside affected ESBs (%)	59.80	62.35	64.76
Building area inside affected ESBs (%)	59.83	63.37	68.03
Average building count per affected ESB	4,439	3,811	3,364
Average building area per affected ESB (km ²)	1.49	1.30	1.19
Grid-line length inside affected ESBs (%)	35.04	41.98	46.59
Average grid-line length per affected ESB (km)	114.25	112.74	106.35

Table 3 adds quantitative context to the mapped ESB patterns. The number of affected ESBs increases from 70 to 100 between the 50- and 500-year scenarios, representing 17.16% to 24.51% of ESBs with assigned substations. Within those affected ESBs, mean closure rises from 29.76% to 40.99%, the average number of closed substations increases from 1.54 to 2.26, and fully closed service areas increase from 7 to 18. These results show that larger flood scenarios do

not only affect more service territories; they also increase the concentration of closed substations within affected ESBs. The affected ESBs also contain a large share of statewide built-environment and grid context.

Overall, the ESB-level results show that footprint-level closures are not confined to isolated facility locations; they appear within service territories that cover a large share of Iowa's built-environment and grid-infrastructure context. The contrast between the relatively small share of affected ESBs and the much larger share of buildings, building footprint area, and grid-line length inside those territories shows why the service-boundary scale adds value beyond county counts and individual substation closures. Because ESBs can contain multiple substations, these results summarize substation closure patterns at the service-territory level and illustrate how facility-level exposure is distributed across utility service areas.

3.4. Influence-Zone Assessment

The Voronoi-based influence-zone assessment provides a substation-centered view of flood exposure by associating each closed substation with its corresponding zone. Unlike counties or ESBs, which aggregate multiple substations within larger reporting boundaries, each polygon is linked to one substation. This structure allows the surrounding building, footprint-area, and grid-line context to be evaluated around individual closed facilities. The interpretation is also sensitive to substation spacing: dense urban networks produce smaller polygons, while wider rural spacing produces larger polygons. Therefore, polygon size reflects the spacing of the substation network, while polygon status reflects whether the associated substation footprint is closed.

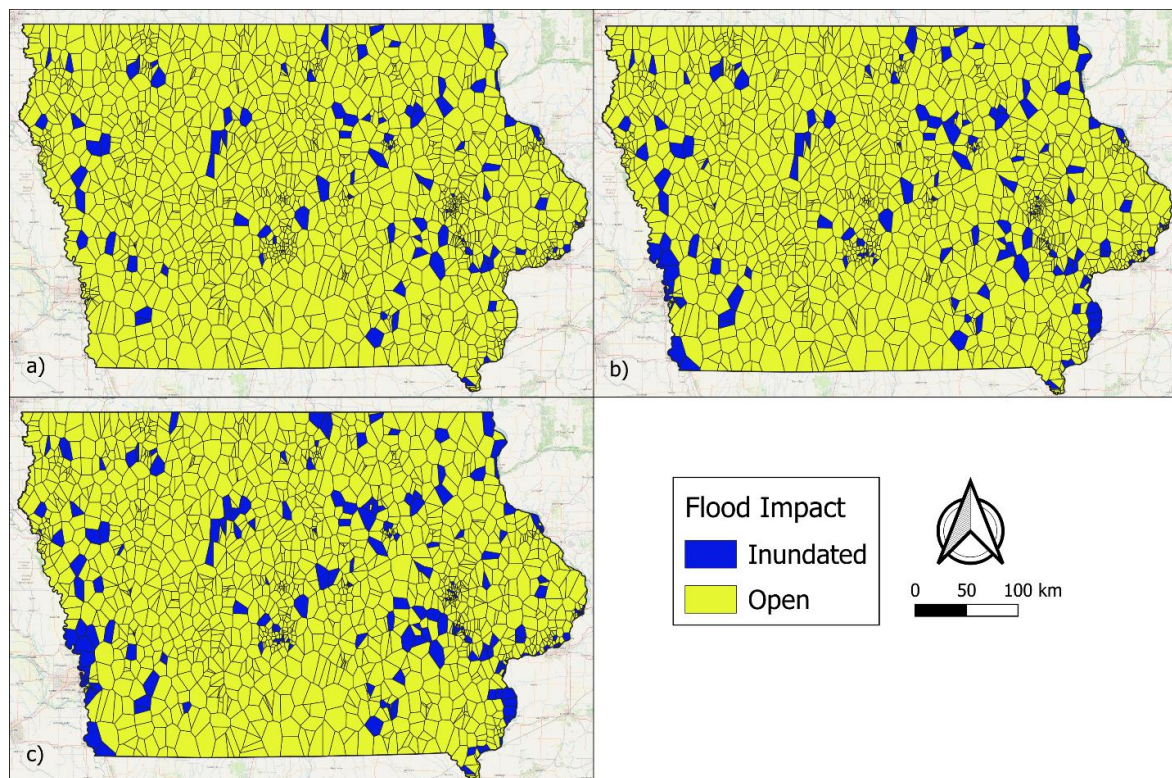


Figure 5. Spatial distribution of affected substation Voronoi influence-zones under the a) 50-year, b) 100-year, and c) 500-year flood scenarios.

Figure 5 presents the affected substation influence zones under the 50-, 100-, and 500-year scenarios. In Figure 5a, the 50-year pattern is dispersed, with affected zones along the western boundary, northeastern edge, east-central Iowa, and southeastern edge. In Figure 5b, the 100-year scenario expands this pattern along the southwest and west-central boundary and adds more affected zones in east-central and eastern Iowa. In Figure 5c, the 500-year scenario shows stronger clustering in east-central and southeastern Iowa, where several affected zones occur close together, indicating that larger flood scenarios begin to involve nearby substations within the same regional network. Western and southwestern affected zones also remain prominent, but many of these polygons are larger because closed substations in those areas are spaced farther apart from neighboring facilities. As a result, larger affected polygons represent closed substations with broader proximity areas, while smaller affected polygons identify closures embedded within denser substation networks.

Table 4 shows the built-environment and grid-line context in the impacted zones. The affected land-area share remains lower than the facility-closure rate in all three scenarios: impacted zones cover 5.52%, 7.73%, and 9.43% of statewide influence-zone area, compared with facility-closure rates of 6.13%, 9.70%, and 12.83%. Because each closed substation is linked to one Voronoi polygon, this gap indicates that the affected set is weighted toward smaller influence zones. In spatial terms, many closed substations occur where substations are spaced more closely, so the mapped land-area footprint of exposure remains smaller than the facility-closure count alone would suggest.

The building indicators show a strong developed-setting signal. Impacted influence zones contain 6.65%, 10.53%, and 14.56% of statewide buildings, while their building-footprint share increases more sharply, from 6.88% to 17.76% across the scenarios. The 500-year comparison is especially informative. Impacted zones occupy 9.43% of statewide influence areas but contain 17.76% of statewide building footprint area. This gap shows that affected substation-centered zones are associated with more developed surroundings, where the physical building footprint is large relative to the mapped influence-zone area. The per-facility values follow the same pattern: buildings per closed substation remain near 312 in the 50- and 100-year scenarios and rise to 326.50 in the 500-year scenario, while mean building footprint area per closed substation increases from 0.11 to 0.13 km². The stronger change in building footprint area compared with building count suggests that developed surface intensity is a key part of the exposure profile.

Table 4. Substation influence-zone exposure-context summary.

Metric	50-year	100-year	500-year
Influence-zone area share (%)	5.52	7.73	9.43
Buildings per closed substation	312.12	312.15	326.50
Building-count share in impacted zones (%)	6.65	10.53	14.56
Building footprint area in impacted zones (km ²)	11.63	20.23	30.01
Building footprint area per closed substation (km ²)	0.11	0.12	0.13
Building-footprint share in impacted zones (%)	6.88	11.97	17.76
Grid-line length per closed substation (km)	12.20	11.24	10.69
Grid-line length share in impacted zones (%)	5.88	8.58	10.79

Grid-line length adds an infrastructure-network dimension to the influence-zone results. Impacted zones contain 5.88%, 8.58%, and 10.79% of statewide grid-line length, which is above their land-area shares in each scenario. This means that affected influence zones contain a somewhat higher concentration of mapped grid infrastructure than area alone would suggest. However, this contrast is weaker than the building-related pattern: grid-line shares remain closer to area shares, and mean grid-line length per closed substation declines from 12.20 to 10.69 km. This pattern suggests that larger flood scenarios add closures in more developed substation surroundings, but not with a proportional increase in nearby mapped line length. Even so, grid-line context remains relevant because lines within affected influence zones help identify where closure locations overlap with access, inspection, switching, and recovery considerations.

The combined spatial and tabular results show that impacted areas occupy a limited land share but contain a larger portion of buildings, building footprint area, and grid-line length. This contrast means that closure counts identify how many substations are affected, while the Voronoi indicators show whether those closures occur in denser and more developed substation-centered zones. The results therefore suggest that footprint-level closures are spatially selective but carry stronger surrounding consequence potential under larger flood scenarios.

3.5. Kernel Density Hotspot Analysis

In this study, kernel density mapping was used to convert closed-substation locations into continuous hotspot surfaces, using the 500-year scenario as the reference case. This scenario provides the most complete closure set in the analysis, so it is better suited for comparing whether closure concentration remains in the same places after the points are weighted by grid length, building area, and building count. Comparing the unweighted closure surface with the weighted surfaces helps distinguish areas where closures are concentrated by count from areas where those closures also carry stronger transmission-network or built-environment context.

Figure 6a identifies the main spatial accumulation of 500-year closed substations. The strongest unweighted pattern appears along eastern and southeastern Iowa near the Mississippi corridor, especially around Scott, Clinton, Muscatine, Louisa, and nearby counties. Additional closure-density pockets appear around Polk County, the Pottawattamie–Mills area, and the Linn–Johnson east-central corridor. In Figure 6b, the grid-length-weighted surface changes the interpretation by emphasizing transmission-line presence around closed substations. Eastern and southeastern Iowa remain visible, but the hotspot emphasis shifts toward Iowa, Johnson, Muscatine, and Louisa counties, where closed substations are associated with longer line length. Pottawattamie also remains prominent because of its western-border position and regional transfer setting.

The grid-weighted surface also introduces northern pockets near Humboldt, Butler, Fayette, and Allamakee; these areas are not dominant in the unweighted or building-weighted maps, but their appearance here points to closed substations with notable line-infrastructure association. Polk County is less dominant in this panel, which is consistent with a transmission-corridor weighting instead of an urban built-environment weighting. In Figure 6c, the building-area-weighted surface emphasizes developed-footprint intensity around closed substations. Polk County becomes the strongest hotspot, unlike the unweighted surface where Polk is visible but

does not dominate the statewide pattern. Additional hotspots appear around Scott/Clinton, Linn/Johnson, Black Hawk, and Pottawattamie.

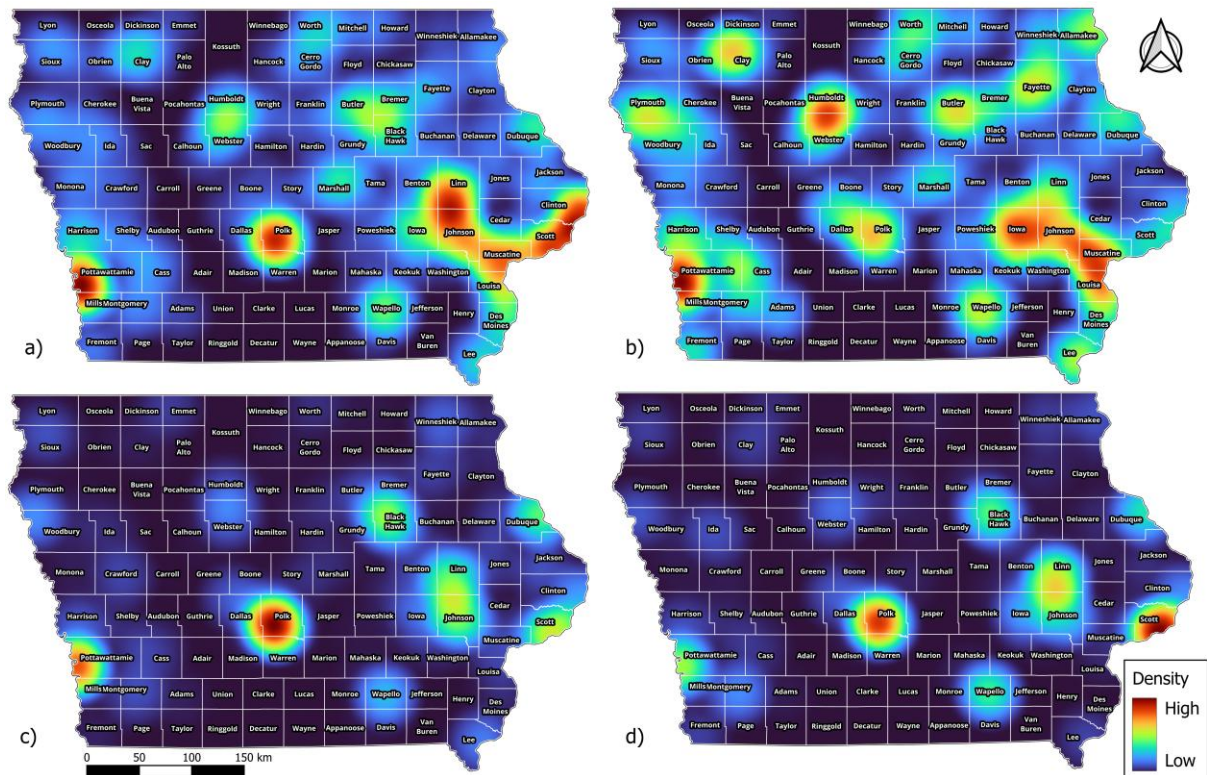


Figure 6. Quartic kernel density maps of 500-year closed substations: a) unweighted closure density, b) grid length-weighted density, c) building area-weighted density, and d) building count-weighted density.

Because building area reflects the physical scale of developed structures, not just the number of building polygons, higher building-area weighting suggests a stronger presence of larger commercial, industrial, institutional, or infrastructure-related development near affected substations. In Figure 6d, the building-count-weighted surface produces a related but more node-centered settlement pattern. Polk remains the strongest localized hotspot, and eastern and southeastern Iowa remain prominent because several closed substations are near development clusters. Scott County shows one of the main differences across the four maps: it is prominent in the unweighted and building-count surfaces, but less dominant in the building-area and grid-length surfaces. This pattern suggests that Scott has a strong building-count setting around closed substations, while Pottawattamie becomes more prominent when the weighting emphasizes developed footprint or grid-corridor conditions.

The kernel results show that hotspot priority depends on the weight assigned to closed substations. The unweighted surface identifies where closures cluster, the grid-weighted surface identifies where those closures intersect stronger transmission-corridor context, and the building-weighted surfaces identify where closures are embedded in more developed surroundings. This distinction is important because a closure cluster, a grid-corridor hotspot, and an urban built-environment hotspot do not represent the same exposure context. The kernel

results therefore translate the 500-year closure set into a spatial prioritization layer, showing which areas remain important across multiple exposure dimensions and which areas become important only when a specific infrastructure or built-environment weight is applied.

3.6. Demographic and Energy Context Evaluation

In addition to physical flood exposure, population and energy-affordability indicators were used to evaluate where substation closures overlap with demand and household energy-cost pressure. This follows critical-infrastructure flood-impact work that links exposed networks with human development (Pant et al., 2018) and energy-affordability research that connects household energy stress to income, housing conditions, energy expenditures, and coping capacity (Hernández, 2016; Dreobl et al., 2020).

Figure 7 combines 500-year substation inundation percentage with population to show whether flood exposure is occurring in low-population infrastructure settings or in places with larger demand context. The strongest combined signal appears in eastern and southeastern Iowa, including Mississippi-side counties and the southeastern corner of the state, where higher closure percentages overlap with higher population. This pattern indicates that exposure in these counties carries a larger demand context than closure percentage alone would show. Western and northwestern counties show a different pattern: closure percentage is visible, but population intensity is lower, so the map points more toward dispersed infrastructure exposure than population-linked exposure. The central-southern interior remains lighter, indicating weaker overlap between population and substation closure percentage. The bivariate map therefore clarifies which closure patterns are mainly infrastructure-driven and which are reinforced by population concentration.

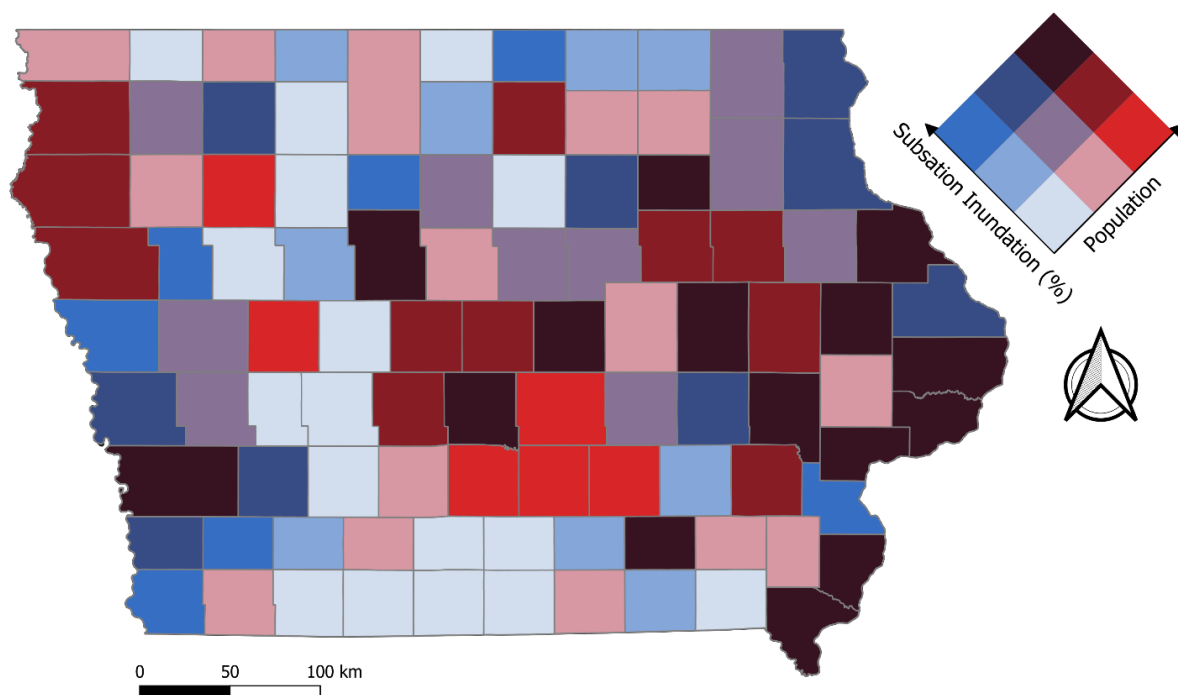


Figure 7. Bivariate county-level map of 500-year substation closure percentage and population using natural breaks classification.

Table 5 presents the population results under the ESB and influence-zone frameworks. At the ESB scale, affected service territories contain a large share of Iowa’s population, increasing from more than half of the statewide population in the 50-year scenario to nearly two-thirds in the 500-year scenario. However, the mean population per affected ESB decreases across scenarios, which shows that larger floods add more service territories, but these additional territories are less populated on average than the earliest affected ones. The influence-zone framework shows a different facility-centered pattern: impacted zones represent a smaller statewide population footprint, but both their population share and the mean population per closed substation increase with flood magnitude. The two trends should therefore be read as separate scale effects: ESB summaries show that affected service territories cover a larger population envelope, while influence-zone summaries show that the closed substations themselves are associated with higher nearby population context.

Table 5. Population context under ESB and influence-zone frameworks.

Level	Metric	50-year	100-year	500-year
ESB	Population in affected ESBs	1.76 m	1.94 m	2.11 m
	Population share in affected ESBs (%)	55.25	60.66	66.27
	Mean population per affected ESB	25,183	22,768	21,142
Influence Zone	Population within impacted zones	241,942	456,535	654,410
	Population share in impacted zones (%)	7.58	14.31	20.51
	Mean population per closed substation	2,240	2,670	2,896

Energy burden and electricity cost were evaluated within the influence-zone framework, so the affordability results remained linked to the substation-centered zones of closed facilities, instead of being averaged across broad service territories. Figure 8 shows that impacted Voronoi zones have mean energy-burden values of 4.05%, 3.74%, and 3.75% across the 50-, 100-, and 500-year scenarios, all above the statewide average of 3.52%. In contrast, mean electricity cost in the same zones is slightly lower than the statewide average, with values of 0.131, 0.129, and 0.129 USD/kWh compared with 0.135 USD/kWh statewide.

This contrast shows that the affected zones include households for which energy costs represent a larger share of income, even under lower average electricity prices. The 50-year scenario has the highest mean burden, suggesting that the earliest affected substations are located within the most energy-cost-sensitive surroundings, while the larger scenarios expand the affected set toward the statewide baseline but remain above it. Energy burden therefore adds a secondary screening signal by identifying where substation flood exposure overlaps with local affordability stress that electricity cost alone would not capture.

The demographic and energy results extend the analysis beyond facility closure by characterizing the population demand and household affordability stress associated with exposed substations. The county bivariate map identifies regional combinations of high closure percentage and population concentration, with the strongest pattern in eastern and southeastern Iowa. At the service-territory scale, affected ESBs include a large share of Iowa’s population; at the facility-centered scale, impacted influence zones show that closed substations are increasingly associated with more populated local surroundings. These same impacted zones

also have energy burden above the statewide baseline, indicating that substation exposure is tied not only to demand concentration but also to household energy-cost sensitivity. Together, these layers help identify exposed facilities where physical flood exposure carries broader social and planning relevance.

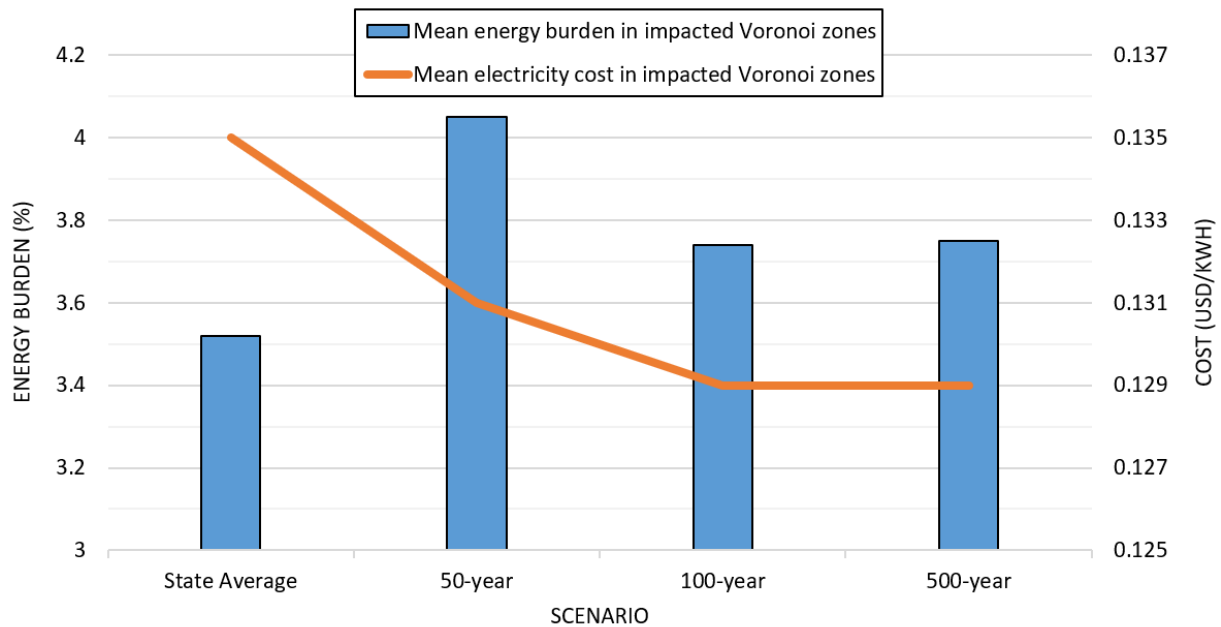


Figure 8. Mean energy burden and mean electricity cost for the statewide baseline and impacted influence zones under the 50-, 100-, and 500-year flood scenarios.

3.7. Allocation Sensitivity and Consistency Analysis

The ESB analysis uses a binary affected boundary rule: an ESB is treated as affected when at least one assigned substation is closed. This rule identifies the service-territory extent associated with substation exposure, but it can inflate population, building, and grid-context totals because the full ESB is counted even when only a small portion of its assigned substations is closed. The sensitivity analysis evaluates whether closure-rate weighting provides a consistent adjustment to this binary ESB assumption. In the weighted ESB estimate, population, building count, building area, and grid-line length are multiplied by the internal closure rate of each ESB. The influence-zone estimate is used as the facility-centered comparison because each closed substation contributes only its own influence zone. The comparison therefore evaluates whether a closure-rate adjusted ESB estimate produces exposure patterns that remain consistent with a direct closed substation allocation.

Figure 9 presents the binary ESB, closure-rate weighted ESB, and influence-zone estimates for population, building count, building area, and grid-line length across the three flood scenarios. The binary ESB values are the largest in every panel because the full service-boundary context is counted after the first substation closure inside an ESB. Closure-rate weighting reduces these totals by scaling each ESB according to its internal closure rate. This adjustment changes the ESB result from a broad service-territory envelope to a severity-adjusted exposure estimate. The population panel shows the strongest scale effect: affected ESBs contain 1.76 to 2.11 million people across the scenarios, while the weighted ESB

population falls to 0.20 to 0.52 million. Closure-rate weighting reduces the broad ESB population total, but the weighted ESB values remain below the influence-zone estimates. This means that population around closed substations is not captured well by distributing ESB population in proportion to closure rate. The influence-zone result is more localized, so it captures population concentrated near the affected facilities more directly.

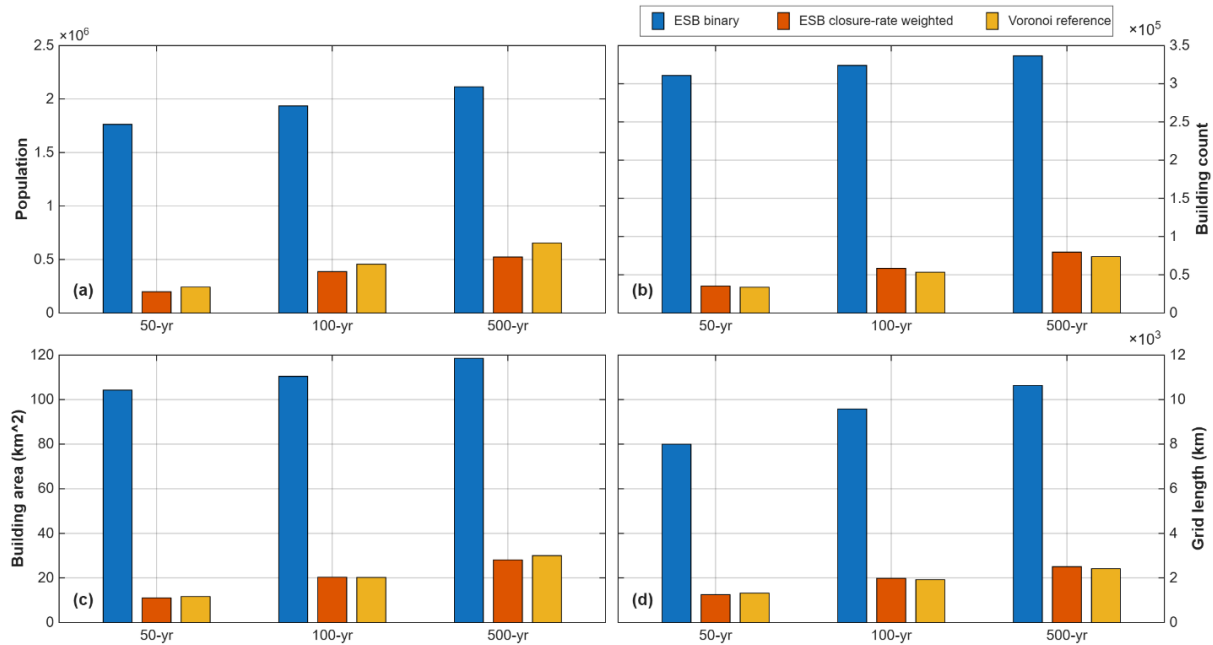


Figure 9 Comparison of binary ESB, closure-rate weighted ESB, and influence-zone reference estimates under the 50-, 100-, and 500-year flood scenarios for (a) population, (b) building count, (c) building area, and (d) grid-line length.

The building variables show stronger consistency after the binary ESB extent is adjusted by closure rate. Building count falls within a similar range in the weighted ESB and influence-zone results, although weighted ESB values remain slightly higher. Building area shows the closest aggregate match between the two severity-sensitive formulations, with the weighted ESB and influence-zone values nearly aligned across the three scenarios. This indicates that developed-footprint exposure remains relatively stable when the analysis shifts from closure-weighted service territories to closed-substation influence zones. Grid-line length also moves closer to the influence-zone total after closure-rate weighting, but this aggregate similarity requires a facility-level check because similar totals can still assign unequal grid-line values to the same closed substations under the ESB and influence-zone frameworks. Figure 9 therefore summarizes the aggregate comparison, while Table 6 evaluates whether individual closed substations receive similar values under both frameworks.

Table 6 evaluates consistency between closure-rate weighted ESB values and influence-zone values at the closed-substation level. Spearman's (ρ) shows whether the two frameworks rank closed substations in a similar order, while Pearson's (r) shows whether the values follow a similar linear pattern. Building area has the strongest consistency, with (ρ) around 0.58–0.61 and (r) around 0.49–0.52, indicating that both the ordering of closed substations and the value magnitudes remain aligned across the two allocation frameworks. Building count also shows

consistent ranking, with (ρ) above 0.51 in all scenarios, but lower (r) values suggesting that the two methods identify the same higher- and lower-building-context substations while the actual values spread differently. Population shows moderate consistency, with (ρ) around 0.37–0.41 and (r) around 0.42–0.49 because of shared demographic signal but stronger boundary-scale effects. However, grid-line length is separated from the other variables. After a modest relationship in the 50-year scenario, both (ρ) and (r) move close to zero in the 100- and 500-year scenarios. This is because line-length context is more dependent on the selected partial unit as flood magnitude increases and more closed substations enter the comparison.

Table 6. Correlation between closure-rate weighted ESB estimates and influence-zone estimates at the closed-substation level.

Scenario	Metric	Spearman (ρ)	Pearson (r)
50-year	Population	0.408	0.475
	Building count	0.564	0.375
	Building area (km ²)	0.588	0.504
	Grid-line length (km)	0.301	0.350
100-year	Population	0.370	0.495
	Building count	0.517	0.309
	Building area (km ²)	0.581	0.487
	Grid-line length (km)	0.066	-0.016
500-year	Population	0.406	0.425
	Building count	0.536	0.349
	Building area (km ²)	0.614	0.525
	Grid-line length (km)	-0.027	-0.047

As a visual complement to the correlation results, Figure 10 presents log-scale scatterplots for the 500-year scenario, because it contains the largest closed-substation set, providing the largest closed-substation sample for comparing facility-level consistency between the two allocation frameworks. A $\log(1+x)$ transformation was applied because the exposure variables are right-skewed and include zero values; this transformation reduces the visual dominance of extreme observations while retaining records with zero building-area or grid-line values (West, 2022; Chen & Roth, 2024). The building-area plot shows the more consistent pattern. Higher building-area values align with higher closure-rate weighted ESB values. The horizontal bands reflect the ESB weighting structure, since closed substations assigned to the same ESB receive the same weighted ESB value even when their influence-zones values differ. The grid-line panel is more dispersed. Similar closure-rate weighted ESB line-length values correspond to a wide range of influence-zone line-length values, and higher influence-zone line-length values do not consistently align with higher weighted ESB values. This visual pattern matches the weak correlations in Table 6.

The sensitivity analysis clarifies how each exposure indicator is tied to the closed substation itself and how much is introduced by the spatial unit used to summarize surrounding conditions. Closure-rate weighting narrows the broad ESB envelope, and comparison with influence-zone values tests whether this adjusted service-territory signal remains consistent at the facility-

centered scale. Building area remains the most consistent indicator across both aggregate and closed-substation-level comparisons, so developed-footprint exposure can be interpreted across ESB and influence-zone results with fewer allocation-related changes. Building count preserves a similar ordering of affected facilities, although its magnitudes differ more. Population reflects the scale at which demand is assigned: ESBs represent broader service-territory population, while influence zones represent local population around closed substations. Grid-line length is more boundary-sensitive because ESB-based line length describes grid setting within affected service territories but does not translate consistently into a closed-substation-level measure. The sensitivity results therefore define the interpretation limits of the multi-scale framework by separating indicators that persist across allocation choices from indicators that depend on the selected spatial unit.

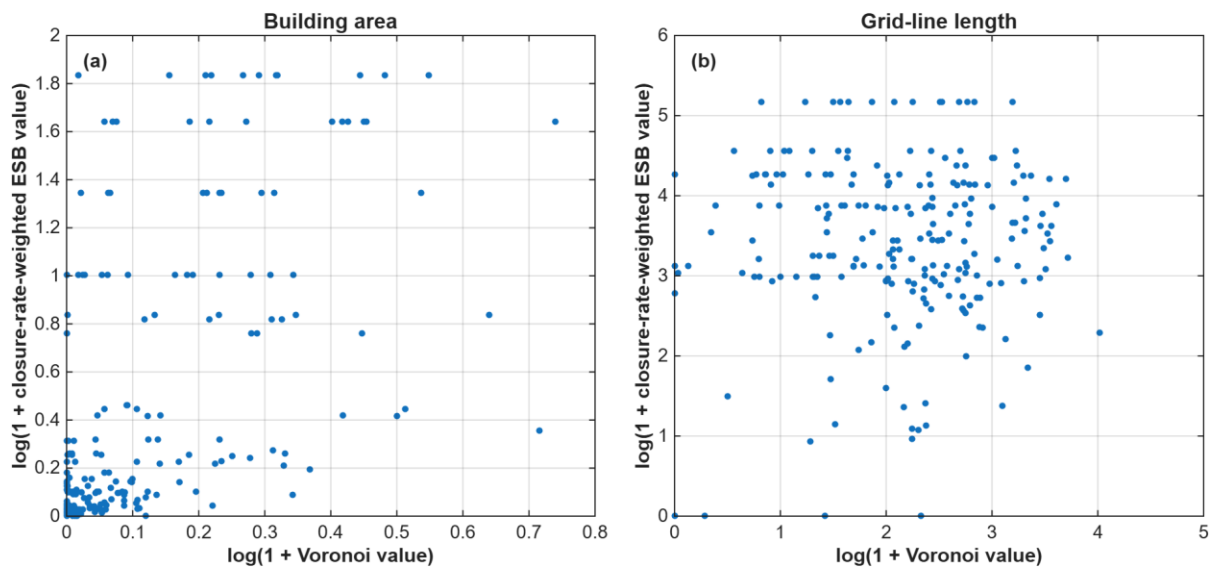


Figure 10. Log-scale scatterplots comparing influence-zone and closure-rate weighted ESB values for closed substations in the 500-year scenario: (a) transmission line length and (b) building area.

4. Conclusion

This study presents a data-driven geospatial framework for assessing flood exposure of electrical substations in Iowa under 50-, 100-, and 500-year flood scenarios. The framework was designed to move beyond a simple exposed/not-exposed facility count by connecting footprint-level inundation with service-territory reach, substation-centered influence zones, population distribution, building concentration, energy burden, grid-line setting, hotspot structure, and allocation sensitivity. This approach offers a practical screening basis for identifying substations and regions where flood exposure should receive closer engineering review, emergency planning attention, mitigation assessment, or policy-level resilience prioritization.

The main finding is that direct substation exposure remains relatively small statewide but becomes more consequential where inundated facilities coincide with corridor, service-territory, built-environment, population, and grid-infrastructure conditions. Larger flood scenarios increase not only the number of exposed substations but also the depth and areal coverage of

inundation inside affected footprints. Spatially, exposure concentrates along eastern and southeastern Iowa near the Mississippi corridor, while western and northwestern border areas reflect transmission-corridor conditions. Polk County represents an urban built-environment case because building-weighted hotspots emphasize dense development around affected substations. At the ESB scale, higher internal closure conditions first appear in eastern and northern service territories, then extend toward eastern Iowa and the western, northwestern, and southern boundary corridors under larger scenarios, meaning that flood exposure should be interpreted through both facility inundation and the infrastructure context around that facility.

The facility-centered results refine this spatial pattern. Affected substation zones become more spatially concentrated in east-central and southeastern Iowa in the 500-year scenario, while larger western and southwestern polygons reflect wider substation spacing. KDE analysis separates closure concentration from the surrounding attributes assigned to each closed substation. Unweighted density emphasizes the eastern and southeastern closure corridors, grid-weighted density shifts toward transmission-corridor areas, and building-weighted density highlights Polk County and other developed urban clusters.

Demographic results connect affected ESBs with broad service-territory demand and substation influence zones with local population exposure. Impacted zones remain above the statewide energy-burden baseline despite lower average electricity cost, so the affordability concern reflects household conditions around exposed substations. The sensitivity analysis indicates that closure-rate weighting makes ESB and influence-zone results most consistent for building footprint areas, whereas grid-line length remains less consistent because transmission lines extend across service territories in ways that are not centered on individual closed substations.

There are several limitations. The closure definition represents mapped footprint-level flood exposure, not confirmed equipment failure, outage occurrence, customer interruption, or power-flow disruption. The flood layers describe modeled 50-, 100-, and 500-year return-period inundation extent and depth, not event-specific flood dynamics; higher-resolution hydrodynamic simulations can capture hazard intensity in greater detail, but their computational, expertise, and local-data requirements limit statewide scalability (Markert et al., 2024). The HUC8-based raster structure and model transitions can also introduce edge effects or non-monotonic exposure artifacts, which required cross-scenario consistency checks.

ESB results describe utility-territory exposure, not feeder-level service relationships, while substation zones represent areas defined by nearest-substation proximity, not actual operating service areas. Therefore, population, building, energy-burden, and grid-line indicators should be interpreted as spatial exposure and consequence indicators, not direct measures of damaged assets or disrupted customers. Within these constraints, the framework offers a transparent statewide baseline for interpreting substation flood exposure across levels, from direct facility inundation to service-territory demand, developed land, affordability conditions, and grid-corridor setting, based on planning needs and available spatial data.

Future work should integrate feeder assignments, outage records, power-flow models, fragility functions, access-route disruption, and restoration data to extend the framework toward operational reliability assessment. Machine learning and AI-based methods could improve footprint refinement, exposure classification, hotspot prediction, outage-risk learning from historical events, and rapid scenario evaluation, while multi-criteria decision analysis

could combine flood depth, facility characteristics, service-territory exposure, building intensity, energy burden, and grid connectivity into a mitigation-prioritization index. User-friendly web tools and interactive dashboards could make the outputs accessible to utilities, emergency managers, and public agencies, and future settlement, land-use, renewable-energy, and climate-adjusted flood scenarios could evaluate how exposure patterns change over time. These extensions would build on the study's main contribution: a transparent, scalable way to connect substation flood exposure with the broader physical and social conditions that shape resilience planning.

Author Contributions

E.D.: conceptualization, methodology, validation, data curation, visualization, formal analysis, and writing—original draft preparation; O.M.: conceptualization, data curation, writing—review and editing, validation, supervision; I.D.: writing—review and editing, validation, supervision, project administration, and funding acquisition.

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